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MOBILE APPLICATION FOR ASTHMA PREDICTION USING FUZZY-CERTAINTY FACTOR EXPERT SYSTEM

FISICHELA THIOANDA¹, FRISKA NATALIA^{1,*}, FERRY VINCENTTIUS FERDINAND²
SUD SUDIRMAN³ AND CHANG SEONG KO⁴

¹Department of Information Systems
Universitas Multimedia Nusantara
Scientia Boulevard, Gading Serpong, Tangerang, Banten 15811, Indonesia
fisichela.thioanda@student.umn.ac.id; *Corresponding author: friska.natalia@umn.ac.id

²Department of Mathematics
Universitas Pelita Harapan
Tangerang, Banten 15811, Indonesia
ferry.vincenttius@uph.edu

³School of Computer Science and Mathematics
Liverpool John Moores University
Liverpool L3 3AF, UK
s.sudirman@ljmu.ac.uk

⁴Department of Industrial and Management Engineering
Kyungshung University
309, Suyeong-ro, Nam-gu, Busan 48434, Korea
csko@ks.ac.kr

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ABSTRACT. *Asthma is a chronic illness that sporadically affects the ability of the person who has it to breathe. It is reported that out of the 417,918 global deaths attributed to asthma in 2016, and the majority occurred in low- and lower-middle-income countries. Asthma sufferers in these countries often do not realize that they have asthma and leave the symptoms untreated because they have limited access to affordable and quality health-care. We propose a methodology to address this issue by bringing the medical experts closer to the poorer segment of the population via a mobile application. The application uses a rule-based algorithm based on a fuzzy-certainty factor model to manage uncertainties that are present when collecting data from the experts and users. The result of the experiment shows that this technique manages to accurately predict the occurrence of the disease and identify the type of the disease with 96.7% accuracy.*

Keywords: Asthma prediction, Expert system, Certainty factor, Mobile App, Android

1. Introduction. Asthma is a chronic illness that sporadically affects the ability of the person who has it to breathe. The illness inflames the air passages of the lungs making them narrow and inflamed. The illness affects people of all ages and often starts in childhood, but it can also develop during adulthood. There is currently no cure for asthma but there are treatments that can help control the symptoms. The severity and frequency of the symptoms can vary depending on the type of asthma, time of days, weather, and temperature, and can get worse during moderate to intense physical activities. The most current estimate by the WHO of the number of people globally who suffer from asthma is above 339 million [1]. The report also estimates that there were 417,918 deaths attributed to asthma at the global level in 2016, the majority of which occurred in low- and lower-middle-income countries. The prevalence of the disease globally is considered under-diagnosed and under-treated, meaning that its sufferers do not often realize that they have

asthma and leave the symptoms untreated. This has created a significant burden to the individuals and their families and often created restrictions on the individuals' ability to carry out productive activities in their lifetime.

Many people who live in low- and lower-middle-income countries have limited access to affordable and quality healthcare. As a result, they often are not able to find out what illness that ails them despite suffering from its symptoms regularly. At the same time, we also recognize that the rate of increase in Internet and smartphone penetration in these countries is increasing rapidly. We see this as an opportunity to address the issue of having limited access to affordable and quality healthcare by bringing the medical experts closer to the poorer segment of the population via mobile technology. We conducted a study to test the urgency of finding the solution to this problem by distributing a questionnaire to 30 respondents in Indonesia. In this study, we found that an overwhelming majority (83.3%) need a mobile application to help them understand asthma either for themselves personally or for the benefit of people they know. A recent survey [2] on the different techniques for asthma prediction shows that the majority of approaches use machine learning techniques such as support vector machine, k -nearest neighbor, AdaBoost, artificial neural networks, and random forest [3]. However, only a few of the existing solutions were implemented as a smartphone application to be used directly by the general public. One of the most recent and the closest smartphone-based solutions was proposed by Sakkatos et al. [4] where a patient's asthma condition for the next 21 days can be predicted based on the measurement of the patient's peak expiratory flow using artificial neural networks. However, this solution requires the use of a peak expiratory flow (PEF) meter with the smartphone. The additional cost of using the PEF device could potentially limit the use of the method by the general public in low- and lower-middle-income countries. It is also important to note that the use of mobile applications has been suggested in the past to help improve patients' healthcare and quality of life, including optimization of patient management in hospitals [5], managing allergy [6], and providing an interactive tool for the visually impaired [7]; however, they did not specifically address the problem of asthma prediction that we described previously. Therefore, we concluded that the scarcity of a solution that addresses the problem necessitates the research we conducted and reported in this paper. The major contribution and significance of our research are the adaptation and application of the certainty factor approach to deal with the absence of reliable statistical information provided by the user of the developed mobile application to classify the type of asthma that they are suffering.

This paper is organized as follows. In the next section, we will discuss how the certainty factor approach can be adapted and applied to analyzing the fuzzy information provided by the user. This is then followed by an analysis and discussion of the experimental results before we present the conclusion of the research.

2. Methodology. Our method to solve the aforementioned problem is by providing a quick, free, reliable, and automated way for ordinary people to find out if they are suffering from asthma. We do this by developing a mobile application that contains a rule-based system developed using knowledge obtained from medical experts. The user of this mobile application is asked a series of questions related to common symptoms of the illness and can respond by entering a number that represents their sureness of experiencing each symptom. The application then predicts if the user is suffering from asthma by calculating its probability using our designed rule-based system that has been adapted to manage uncertainties in both the experts' opinions and user's responses using a modified certainty-factor (CF) method [8]. The outline of our proposed methodology is illustrated in Figure 1. Although the use of the CF method to detect diseases has been proposed in the past by Hasdiana et al. [9], our approach is substantially different. In that paper, the authors attempt to diagnose ten categories of diseases on one single patient

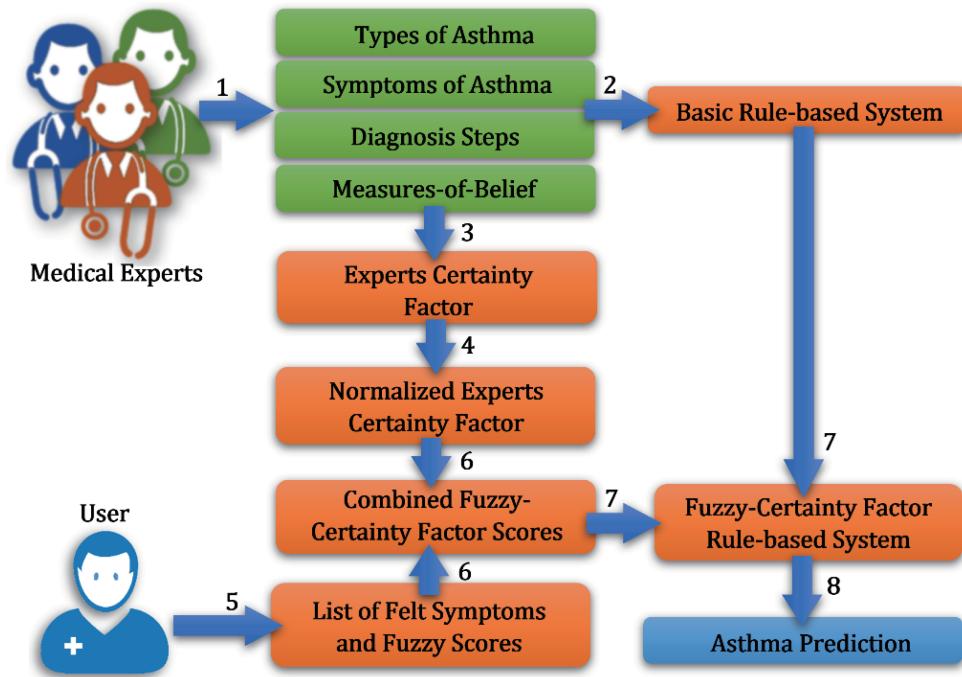


FIGURE 1. The outline of the proposed methodology. The steps are as follows: 1) Opinions from medical experts are collected to produce the basis of information for our rule-based system, 2) construction of a basic rule-based system, 3) calculation of certainty factor based on the experts' average measure-of-belief, 4) normalization of the experts' certainty factor, 5) Taking data from the user on the symptoms and their fuzzy scores, 6) combining the user input and the experts' rules, 7) using the fuzzy-certainty factor in the modified rule-based system to 8) predict if the user has asthma and the type of asthma.

from observation of 48 symptoms using the basic CF method whereas ours concentrate on a single type of disease with more symptoms from multiple patients.

We collected the opinions of several general practitioners with 5 to 29 years of experience on the types and symptoms of asthma, their thought process when diagnosing the illness, and their measures-of-belief on the importance of each symptom to the outcome of the positive diagnosis of asthma. The result of our experts' opinion collection process reveals that there are 19 common symptoms of asthma and three different types of the disease, namely intermittent asthma, mild persistent asthma, and moderate persistent asthma. Each type of asthma can exhibit some combinations of the 19 different symptoms of asthma as summarized in Table 1.

From this table, we can derive a 19×3 matrix R whose elements $R_{(s,p)}$ are binary numbers and take a value of 1 if the cell in the s th row and p th column is ticked, or 0 otherwise. The transpose of R is shown in Table 2.

This piece of information is then used to develop a basic rule-based system that represents the experts' train of thought when diagnosing and deciding the type of asthma based on the state of each observed symptom s_1 to s_{19} . This rule-based system is shown in Table 3.

In practice, the application of this basic rule-based system creates an inflexible asthma prediction process because it does not capture the experts' opinions on the importance of each symptom to the outcome of the positive diagnosis of asthma. Furthermore, this type of rule-based system does not take account of the level of uncertainty when the system is used by non-medical experts when they input to the system the information on the type

TABLE 1. The three types of asthma and their symptoms

Symptoms	Types of asthma		
	Intermittent (P_1)	Mild persistent (P_2)	Moderate persistent (P_3)
Excessive mucus production (s_1)	✓	✓	✓
Coughing happens once in a while in a day (s_2)	✓		
Trouble breathing (accompanied with or without whistling sound) (s_3)	✓		
Chest tightening (s_4)	✓	✓	✓
Attacks happen less than or once in a week (s_5)	✓		
Night-time attack happens less than twice in a month (s_6)	✓		
No disturbance during sleep (s_7)	✓		
No disturbance during activity (s_8)	✓		
Coughing happens a few times in a day (s_9)		✓	
Trouble breathing with whistling sound (s_{10})		✓	✓
Attacks happen more than once in a week (s_{11})		✓	
Night-time attack happens around twice in a month (s_{12})		✓	
A minor disturbance during sleep (s_{13})		✓	
A minor disturbance during activity (s_{14})		✓	
Coughing continuously (s_{15})			✓
Attacks happen almost every day in a week (s_{16})			✓
Night-time attack happens between 3 or 6 times in a month (s_{17})			✓
Trouble while sleeping (s_{18})			✓
Limited activity (s_{19})			✓

TABLE 2. The transpose of the 19×3 matrix R as a compact representation of the combination of symptoms of each asthma type

1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0
1	0	0	1	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0
1	0	0	1	0	0	0	0	0	1	0	0	0	0	1	1	1	1	1

TABLE 3. A basic rule-based system to decide the type of asthma

Rule	IF	THEN
1	$s_1 \wedge s_2 \wedge s_3 \wedge s_4 \wedge s_5 \wedge s_6 \wedge s_7 \wedge s_8$	P_1
2	$s_1 \wedge s_4 \wedge s_9 \wedge s_{10} \wedge s_{11} \wedge s_{12} \wedge s_{13} \wedge s_{14}$	P_2
3	$s_1 \wedge s_4 \wedge s_{10} \wedge s_{15} \wedge s_{16} \wedge s_{17} \wedge s_{18} \wedge s_{19}$	P_3

of symptoms they experience. We developed an algorithm and a new rule-based system to address this problem. Our algorithm for the asthma prediction is based on the CF model that was originally developed by Shortliffe and Buchanan for managing uncertainty in a rule-based system [10]. In addition, we incorporated a fuzzy approach to this method to manage additional uncertainties that are present when collecting data from the user. The description of the algorithm is given as follows.

The probability, p , that the user is suffering from a type of asthma is calculated as the cumulative certainty K_N , which is a combination of N number of certainty factors

CF_s of an asthma symptom s , $s \in S$ where S is a set of all asthma symptoms. Hence, mathematically, the probability p is expressed as:

$$p = K_N \quad (1)$$

$$K_n = K_{n-1} + CF_n \times (1 - K_{n-1}) \quad (2)$$

$$K_1 = CF_1 \quad (3)$$

where $n = 1, 2, 3, \dots, N$ and $N = \text{card}(S)$, the total number of symptoms in set S .

Each doctor was asked to provide a number between 0 and 1 as their *measure-of-belief* MB_s that a symptom s is important in their diagnosis of asthma. The average value \overline{MB}_s is then calculated from all responses. From this, we can calculate the experts' certainty factors CE_s as:

$$CE_s = \overline{MB}_s - \overline{MD}_s \quad (4)$$

$$\overline{MD}_s = 1 - \overline{MB}_s \quad (5)$$

We then normalize the values by dividing them by twice the maximum CE_s for $\forall s$ to get \widehat{CE}_s

$$\widehat{CE}_s = \frac{CE_s}{2 \times \max_{\forall s}(CE_s)} \quad (6)$$

We refer to this entity as the experts' normalized certainty factors and use it as a measure of the experts' certainty that a symptom s is important in their diagnosis of asthma in Table 4.

TABLE 4. The experts' mean measures-of-belief, certainty factors, and normalized certainty factors for each symptom

Symptoms	\overline{MB}_s	CE_s	\widehat{CE}_s
s_1	0.7	0.4	0.39
s_2	0.5	0.0	0.28
s_3	0.9	0.8	0.50
s_4	0.7	0.4	0.39
s_5	0.9	0.8	0.50
s_6	0.9	0.8	0.50
s_7	0.9	0.8	0.50
s_8	0.9	0.8	0.50
s_9	0.5	0.0	0.28
s_{10}	0.9	0.8	0.50
s_{11}	0.8	0.6	0.44
s_{12}	0.9	0.8	0.50
s_{13}	0.9	0.8	0.50
s_{14}	0.9	0.8	0.50
s_{15}	0.8	0.6	0.44
s_{16}	0.9	0.8	0.50
s_{17}	0.9	0.8	0.50
s_{18}	0.9	0.8	0.50
s_{19}	0.9	0.8	0.50

The value of CF_s used to calculate the probability p in Equation (1) is the product of the normalized experts' certainty factors with the user's sureness that he or she is experiencing the symptom s , an entity which we denote as CU_s .

$$CF_s = \widehat{CE}_s \times CU_s \quad (7)$$

The process of retrieving CU_s from the user is by asking how sure he or she is experiencing each of the 19 symptoms by letting the user answer the question by selecting one of the preset choices. The choice of allowing the user to select one of the preset responses instead of answering with a binary (yes or no) answer would effectively add an element of fuzziness to the response. One example of the question is shown in Table 5.

TABLE 5. An example of the questions posed to the users to retrieve their sureness of suffering an asthma symptom

How sure are you that you are experiencing this symptom?	
S1: Excessive mucus production	
Answer (select one that is most applicable)	Fuzzy score
A. Definitely Yes	1
B. Maybe Yes	0.8
C. Unsure	0.5
D. Maybe Not	0.2
E. Definitely Not	0

The asthma prediction is carried out by calculating the probability value p with Equation (1) using the value of CF_s derived from Equations (2)-(7) and comparing the result with a threshold value T . The binary asthma prediction P_A is determined as follows:

$$P_A = \begin{cases} 1 & p \geq T \\ 0 & p < T \end{cases} \quad (8)$$

If a positive prediction is given, then the system would proceed with determining the most likely type of asthma that the user experiences. This is done by calculating the dot product of CU_s with each column of matrix R in Table 2. This will produce the probability p_{type} of the user having that *type* of asthma. The final prediction P_{type} is carried out by finding the one that has the maximum p_{type} value.

$$p_{type} = \text{dot}(R_{(s,:)}, CU_s) \quad (9)$$

$$P_{type} = \arg \max_{type}(p_{type}) \quad (10)$$

3. Experiment Results and Discussion. We implemented the system as an Android-based mobile application called "Asthma Care". In addition to having this asthma prediction feature, the application also has other features including an asthma information page, asthma support page, and finding nearest general practitioners who can help with the user's medical complaints. A screenshot of the application is shown in Figure 2.

With respect to testing and evaluating the proposed methodology, we asked thirty participants to take part in our experiment. Five participants are known to suffer asthma while the rests, though suffer from several of the symptoms, are not asthmatic. We also enlisted the same group of medical experts who helped develop the rule-based system to validate the results. The threshold value T used for the binary prediction is set to 0.85. The breakdown of the diagnosis results for all participants is shown in Figure 3. The last row in the figure shows the actual type of asthma of the user as diagnosed by the medical expert whereas the third and second last rows show the diagnosis (positive or negative) and the asthma type if applicable. From the figure, we can see that the system manages to identify correctly all cases except one, which is participant number eight. We looked at

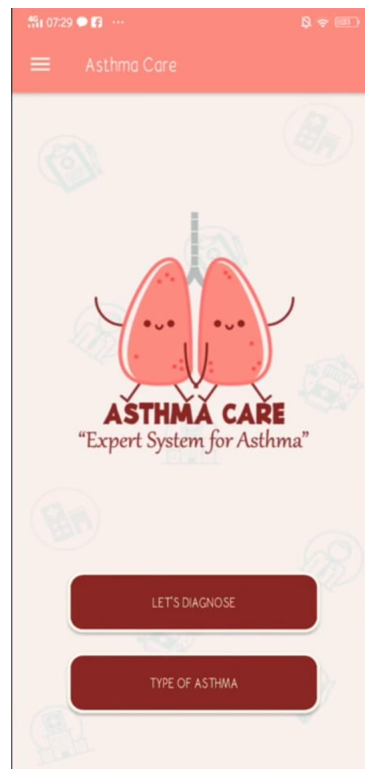


FIGURE 2. The main page of the developed mobile application titled Asthma Care

Symptoms	Participants																													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	0.5	0.5	0.8	1	0.5	0.2	0.8	0.8	0	0	0	0.8	0.5	0	0.8	0.8	0.8	0.8	0.5	0.5	0	0	0.5	0.5	1	0.8	0.5	0.2	0.2	0
2	0.2	0.2	0.8	0	0	0	0	0.5	0	0	0	0	0	0	0.8	0	0	0	0	0	0	0	0.5	0	1	0	0	0	0	0
3	0.2	0.8	0.8	0.8	0	0	0	0.5	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
4	0.2	0.2	0.8	0	0	0	0	0.5	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0.5	1	0	0	0	0	0
5	0.2	0	0.2	0	0	0	0	0.5	0	0	0	0	0	0	0.2	0	0	0	0	0	0	0	0	0	1	0	0	0	0.2	0.2
6	0.2	0	0.2	0	0	0	0	0.5	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
7	0	0	0.2	0	0	0	0	0.5	0	0	0	0	0	0	0.8	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
8	0	0	0	1	0	0	0	0	0	0.5	0.5	0.5	0	0.5	0	0	0	0	0	0	0	0	0	0	1	0.5	0	0	0	0
9	0	0	0	1	0	0.2	0	0	0	0	0	0	0	0	0.2	0	0.8	0.8	0	0	0	0.2	0.2	0	0.5	0	0	0.2	0	0
10	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0	0.2	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0
11	0	0	0	0.5	0	0	0	0	0	0	0.5	0.5	0	0	0.2	0	0	0	0	0	0	0	0	0	0.5	0.2	0	0	0	0
12	0	0.8	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0
13	0	0	0	0.5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0.5	0.2	0	0	0	0.5	0	0	0	0.2	0	0.2	0	0	0	0	0	0	0.2	0.2	0.2	0
15	0	0	0	0	0	0	0	0.5	0	0	0	0	0.8	0.5	0	0	0	0	0	0	0	0	0	0.5	0	0.5	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.2	0	0	0	0	0	0	0	0	0	0.2	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0.8	0.5	0	0	0	0	0	0	0	0	0	0.5	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0.2	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0.5	0.2	0	0	0	0.2	0	0.2	0.2	0	0.2	0	0	0	0	0	0
Diagnosis	Neg.	Neg.	Neg.	Pos.	Neg.	Neg.	Neg.	Neg.	Neg.	Neg.	Neg.	Neg.	Neg.	Pos.	Pos.	Neg.	Neg.	Neg.	Neg.	Neg.	Neg.	Neg.	Neg.	Neg.	Pos.	Neg.	Neg.	Neg.	Neg.	Neg.
Type	N/A	N/A	N/A	P2	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	P3	P1	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	P1	N/A	N/A	N/A	N/A	N/A
Actual	N/A	N/A	N/A	P2	N/A	N/A	N/A	P1	N/A	N/A	N/A	N/A	N/A	P3	P1	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	P1	N/A	N/A	N/A	N/A	N/A

FIGURE 3. The breakdown of the diagnosis results for all participants

this case closely and found out that the calculated probability p value of this participant is 0.849 and it is just 0.001 below the threshold. Overall, our proposed methodology managed to identify correctly the type of asthma that 29 out of the 30 participants have and which translates into an accuracy of 96.7%.

4. Conclusion. We have proposed a methodology for providing a quick, free, reliable, and automated way for ordinary people to find out if they are suffering from asthma. This is achieved through the development of a mobile application that contains a rule-based system developed using knowledge obtained from medical experts. The application works by asking a series of questions related to common symptoms of the illness to the user who can respond by entering a number that represents their sureness of experiencing each symptom. The application predicts if the user is suffering from asthma by calculating its probability using our designed rule-based system that has been adapted to manage

uncertainties in both the experts' opinions and the users' responses. Our experiment shows our proposed methodology has achieved an accuracy of 96.7% when tested using a group of thirty participants. In the future, we plan to include more types of asthma to diagnose and deploy the application to the wider public to make a more comprehensive and universal solution to the problem.

REFERENCES

- [1] The World Health Organization, *Asthma*, <https://www.who.int/news-room/fact-sheets/detail/asthma>, Accessed on 30-Oct-2020.
- [2] G. V. Gayathri and S. C. Satapathy, A survey on techniques for prediction of asthma, in *Smart Intelligent Computing and Applications. Smart Innovation, Systems and Technologies*, S. Satapathy, V. Bhateja, J. Mohanty and S. Udgata (eds.), Singapore, Springer, 2020.
- [3] J. Gaudillo et al., Machine learning approach to single nucleotide polymorphism-based asthma prediction, *PLoS One*, vol.14, no.12, 2019.
- [4] P. Sakktos, T. Antalffy and N. Pavlovskaja, Prediction of peak expiratory flow of the next day through a smartphone application designed for individuals with asthma, *Eur. Respir. J.*, vol.56, no.suppl 64, 2020.
- [5] G. Seannery, Yacob, N. Chandra and D. David, Optimization of hospital patient management in hospitals with Android-based applications, *ICIC Express Letters*, vol.14, no.3, pp.211-217, 2020.
- [6] A. Halim, F. N. Ferdinand and C. S. Ko, Ontology-based decision support system for hypersensitivity disorder allergy, *ICIC Express Letters*, vol.12, no.8, pp.847-854, 2018.
- [7] Z. P. Putra, D. Setiawan, B. Priambodo, Y. Jumaryadi and M. D. Anasanti, Multi-touch gesture of mobile auditory device for visually impaired users, *The 2nd International Conference on Broadband Communications, Wireless Sensors and Powering (BCWSP)*, pp.90-95, 2020.
- [8] E. Roventa and T. Spircu, Certainty factors theory, in *Management of Knowledge Imperfection in Building Intelligent Systems. Studies in Fuzziness and Soft Computing*, Berlin, Heidelberg, Springer, 2009.
- [9] H. Hasdiana, E. R. Syahputra, A. R. Dewi, T. H. Sinaga and Y. A. Dalimunthe, Certainty factor for early detection of children's respiratory disease, *Journal of Physics: Conference Series*, vol.1361, 2019.
- [10] E. H. Shortliffe and B. G. Buchanan, A model of inexact reasoning in medicine, *Math. Biosci.*, vol.23, nos.3-4, pp.351-379, 1975.